REMOTE SENSING

INTRODUCTION

In this article, remote sensing refers to the acquisition of information from digital geospatial data acquired from an overhead perspective, using sensors which sample and record electromagnetic radiation in one or more regions of the electromagnetic spectrum that is reflected or emitted from the surface of the earth. A broader definition might include analog data, other force fields (seismic, acoustic, or gravitational) and non-terrestrial applications (lunar and planetary surfaces and astronomical investigations). However, the above definition provides sufficient scope to describe the data and methods that are commonly considered under the heading of remote sensing.

Remote sensing can trace its origins back to the earliest overhead photography, carried out from balloons during the American Civil War. Aerial photography was well established by the end of World War I, in a decade which also saw the beginning of the science of photogrammetry. Significant developments in the period around World War II included the development of technology to make measurements in the infrared and microwave regions of the electromagnetic spectrum. These technologies became available for civilian use in the 1950s and 1960s. The first meteorological satellite was launched in 1960, and the term "remote sensing" came into widespread use during this decade. Landsat 1, launched in 1972, was the first of a series of earth resource satellites which today provide repetitive multispectral coverage of the earth in digital format. Hyperspectral instruments capable of recording electromagnetic radiation in tens to hundreds of spectral bands simultaneously were deployed in the 1980s on airborne platforms, and became spaceborne at the end of the century. As more types of coverage becomes available at increased spatial and spectral resolutions, almost every natural science—ecology, geology, hydrology, oceanography, atmospheric science — and many areas of economic importance — agriculture, mineral exploration, urban planning, environmental monitoring — are developing new ways to exploit this huge reservoir of data.

The ultimate goal of remote sensing is to extract information from remotely sensed data about the material properties of the earth's surface and of the atmosphere together with their geographical relationships. However, the remote measurements are not controlled exclusively, or even directly, by the variables of interest at the surface of the earth (Verstraete et al. [81]). Therefore, an understanding of the physical basis for remote sensing and the characteristics of remote sensing data is necessary to guide the modification of statistical and other standard methods for extracting information from data. Generally several preprocessing steps are required before such methods can be applied. These include the correction of geometric and radiometric distortions in the data as well as feature extraction for more efficient data processing.

The first and most common product of data analysis is a thematic map, that is, a classification of the areas and features in the scene. Examples of the types of classes of interest include soil and rock types, classification of crops and forests, delineation of ice and snow cover, and identification of land use in urban and suburban areas. Even where mapping is not an end in itself, classification is usually a prerequisite to further analysis. Remote sensing is also used to detect the presence, or confirm the absence, of a specific target class: mineral potential, insect infestations, militarily significant activity, environmental releases from industrial facilities, indications of prehistoric land use, habitat for a given species.

Increasingly, remote sensing data can be interpreted quantitatively. Historically, area and counts were the principal quantities that could be estimated by standard photogrammetric methods and even using data from broad-band multi-spectral instruments. New data types, better calibration methods, and combinations of data types are rapidly extending this list. Spectral unmixing techniques move away from simple classification toward estimates of constituent abundance. Hyperspectral data, used in conjunction with spectral libraries, offer the possibility of quantifying relative concentrations of specific minerals in rocks or soils (van der Meer and Bakken [79]) and chemical species in atmospheric plumes (Mattu et al.

[54]). Current earth observation satellites such as Terra (launched in December 1999) carry multiple instruments and expect to quantify three-dimensional distributions of aerosols, ozone and water vapor in the atmosphere as well as air, land and sea temperatures and terrestrial and ocean productivity (King & Herring [46]).

The lengthy bibliography at the end of this article forms a minute but representative sample from the enormous literature on remote sensing and is intended to provide a starting point for further reading.

THE NATURE OF REMOTE SENSING DATA

The overhead perspective mentioned in the working definition of remote sensing given above comes from deploying remote sensing instruments on airplanes or satellites. As these platforms move along their flight paths the instruments typically scan across a swath perpendicular to the direction of motion. The data from a series of such swaths forms a two-dimensional image. Most earth-observation satellites have near-polar sun-synchronous orbits, providing repetitive coverage with a period on the order of 10 to 40 days of each point on earth at the same local time of day. Once launched, there is limited control over data collection by these satellites, although modern instruments have an increasing number of programmable features. Airborne coverage can be more specifically targeted to meet customer demands. Geosynchronous satellites whose position above a point on the surface of the earth is approximately fixed are used primarily for meteorological and communications purposes.

The airborne and spaceborne instruments measure electromagnetic radiation which has been modulated by the surface of the earth and by the atmosphere between the radiation source, the surface and the sensor. The radiation source may be the sun, materials on the surface or in the atmosphere, or the instrument itself. Some parts of the electromagnetic spectrum are not useable for earth-based remote sensing applications because gases in the atmosphere (primarily ozone, carbon dioxide and water vapor) absorb most or all of the energy at certain frequencies. Reflected solar energy is measured in the visible/near-IR part of the spectrum, about 0.4 to 2.5 μm. The thermal signal from sources such as fires is strongest in the mid-IR region, 3 to 5 μm, while re-radiated energy from the sun and cooler atmospheric plumes is measured in the thermal IR region, 8 to 14 μm.

Microwave energy is generally recorded by active sensors such as radar (an acronym for Radio Detection and Ranging.) Remote sensing radars emit pulsed coherent radiation at wavelengths between 1 and 30 cm and measure the reflection of that energy from the earth's surface or from reflectors in the atmosphere. Energy at these frequencies can penetrate cloud cover and supplement the incomplete observations possible at higher frequencies. Lidar (Light Detection and Ranging) applies the same principles in the optical and near-infrared region of the spectrum, and is particularly useful for atmospheric research.

The data acquired by digital spectral remote sensing instruments can be characterized in three "dimensions": spatial, spectral and radiometric. Additional information may be available from multiple passes (time dimension) or from multiple look angles (directional dimension).

Spatial characteristics. A single sensor integrates the energy received across the instantaneous field of view (IFOV) to produce an electronic signal whose magnitude depends on the nature of the observed scene (the average radiance in the prescribed spectral band) and on the dwell time. Hyperspectral instruments include a dispersion element (a diffraction grating or an interferometer) to separate out the components of this signal by wavelength. The nominal dimensions of the IFOV vary from approximately 1-10 km for weather and marine observation satellites down to 5-250 m for earth resource multi-spectral and satellite-mounted radar systems. For aircraft-mounted systems the physical dimensions of the IFOV depend on altitude and scanning direction, so instrument capabilities are generally expressed in angular units (mrad). At typical altitudes the IFOV of an airborne instrument 3-30 m at nadir (i.e., when the instrument is pointed straight down). The imaged swath across the track of a satellite, on the order of 1000 pixels, is from tens to hundreds of kilometers wide. The imaged swath from an aircraft may also be several kilometers although this will require a large angular sweep.

Spectral characteristics. Broad-band multispectral instruments such as the thematic mappers on Landsat satellites integrate emitted or reflected energy over spectral bands that are on the order of 0.1 μm

(in the visible region) to 2 μm (in the mid- and thermal IR regions) wide, for a total of up to six or eight spectral bands. Imaging spectrometers have spectral resolutions on the order of 0.01 μm and up to 200 or more spectral bands. These narrow spectral bands do not have sharp cutoffs however, and the measured signal generally includes some out-of-band response. Radar instruments typically use only a small number of discrete wavelengths.

Radiometric characteristics. Several properties of electromagnetic radiation can be measured: intensity, phase, and polarization. Of these, intensity is most frequently used. The resolution of digital intensity data is reported in bits, between 6 bits (i.e., 64 quantization levels) and 10 bits (1024 levels) for most remote sensing instruments. In general this quantization effect is small relative to the signal-to-noise ratio (SNR) of the receiver, which in turn is limited by the fact that the target area is distant and heterogeneous, and the dwell time is short. In addition, measured radiance is a function not only of surface reflectances but of other factors including topographic shading and atmospheric transmission. Scattering and absorption of radiation by aerosols is the most significant and variable of these atmospheric effects at short wavelengths (visible and near IR.) Speckle (coherent scattering) is the primary limitation on the radiometric resolution of radar images.

Radar sensors can be used to determine topography to high precision (centimeters) and to measure the surface reflectivity or backscatter as a function of the frequency, polarization and illumination direction of the sensing signal. When used as an altimeter, direct use is made of the phase information in the returned signal. Scatterometry uses both the intensity and the polarization of the electromagnetic radiation. Objects which are comparable to or large relative to the wavelength appear bright, while those which are small appear dark, so that to first order what is being measured is surface roughness. However, backscatter is also sensitive to the orientation of an object or surface with respect to the sensor and to the target's electrical properties, including water content. Imaging radars (synthetic aperture radars, or SARs) create intensity images as a function of frequency and using all four combinations of sending and receiving polarization states. Rain mapping radars provide lower resolution, three-dimensional volumetric image of rain regions.

Time dimension. The near-polar, sun-synchronous paths of most orbiting satellites means that their tracks on the earth's surface are approximately periodic. Depending on the configuration of an instrument aboard the satellite, repeat coverage is obtained with various frequencies. For Landsat thematic mapper imagery, for example, the repeat period is on the order of 14 days. The MODerate-resolution Imaging Spectroradiometer (MODIS) aboard Terra images the entire surface of the earth every one to two days, although the satellite itself has a typical period of 16 days.

Directional information. Several airborne and, more recently, spaceborne instruments are capable of acquiring off-nadir imagery by looking forward and backward along the flight path. Views of the same terrain from different angles provides information about the bi-directional reflectance function (BDRF) of vegetation canopies, used to identify their structural and architectural characteristics. The Multiangle Imaging SpectroRadiometer (MISR) aboard Terra collects nine simultaneous images in different directions, which are combined using stereoscopic techniques to obtain three-dimensional information about aerosols, clouds and smoke plumes in the atmosphere. Multiple look information also improves estimates of total reflected flux from the earth's surface (albedo).

One final characteristic of remote sensing data is obvious but significant: its enormous volume. This aspect, no less than the spatial and spectral character of the data, drives much methodological development. Tradeoffs are also made among the various dimensions listed above in designing instruments. For example, MODIS offers a relatively large field of view (250 to 1000 m) and a modest number of spectral bands (36) in exchange for its high resolution in the time dimension. MISR has only four spectral bands but collects nine images with a spatial resolution of about 275 m at each pass. The nature of these compromises reflects the primary mission of the Earth Observing System.

CORRECTING GEOMETRIC AND RADIOMETRIC DISTORTION

Preprocessing of remote sensing data must precede interpretive tasks. Spatial or geometric distortion in the image arises from several sources. These include the curvature and rotation of the earth, the wide field of view and platform instability (both of which are bigger problems for airborne sensors than for satellite instruments), and panoramic effects of scanning instruments. Radar data is affected by the relationship between terrain slope and look angle. While the theory behind the correction of geometric distortions is usually straightforward, its implementation may not be. One problem is registering the image to a rectified grid. (The same problem arises when two or more images or maps from different sources are overlain, another common preliminary to data analysis.) Polynomial interpolation methods are satisfactory for single-band images and have been used for multispectral broad-band data as well. For hyperspectral data, however, simpler nearest-neighbor resampling schemes may be preferred because these do not distort spectral characteristics which will be used for spectral matching and detailed identification of objects in the scene. Detailed geometric correction models are developed for instruments with high spatial resolution (Lee et al. [49][50]).

Pre-flight and in-flight calibration methods as well as image postprocessing are used for radiometric calibration of multispectral instruments. These methods attempt to correct for differences among sensors which cause striping and other systematic effects in the resulting images (relative calibration) and to adjust the sensors so that the digital counts can be accurately related to the radiance at the entrance pupils (absolute calibration.) Calibration sources are carried on board most satellites, and sensors are also pointed at objects such as the moon, test sites on earth such as White Sands, New Mexico, and deep space.

Radiometric distortions are introduced by the atmosphere between the surface and the sensor. Scattering in the atmosphere causes fine detail in image data to be obscured, and the effect is larger at the edges of the swath. Scattering is wavelength dependent, and is also a function of relative humidity, atmospheric pressure, temperature and visibility (a measure of the concentration of larger particles or aerosols in the atmosphere.) Conversion of top-of-atmosphere reflectances into surface reflectances requires ancillary information such as estimates of visibility (particulate concentration) and relative humidity (Ferrier [22].) When such information is unavailable, bulk correction methods that do not require such data may be used. However, newer instruments incorporate correction algorithms based on detailed radiative transfer modeling (Carrère et al. [11], Berk et al. [5], Vermote et al. [80]).

FEATURE EXTRACTION

The corrected remote sensing data set is a large "data cube" with two spatial dimensions and one spectral dimensions, in which each piece of information is proportional to the radiometric energy associated with one pixel in one spectral band. Occasionally a fourth dimension is present in the form of time or direction. Sometimes the directional information is converted into a third spatial dimention. The data could be viewed as set of K-dimensional vectors, where K is the number of spectral bands, indexed by the non-spectral dimensions of the data cube. However, a data cube is not simply a set of independent K-dimensional observations; much structure is associated with the other dimensions. The extraction of information from remote sensing data frequently begins with the assembly of a relevant set of features to which statistical and other algorithms can be applied.

Some simplifying spectral transformations are based on prior information about the reflectance properties of the materials of interest. An example is the Normalized Difference Vegetation Index (NDVI), which is calculated from the reflected solar radiation in the near-infrared (N=0.725-1.1 μm) and red (R=0.58-0.68 μm) wavelength bands as

$$\mathrm{NDVI} = \frac{\mathrm{N} - \mathrm{R}}{\mathrm{N} + \mathrm{R}} \ .$$

Several other band ratio transformations are widely used in interpreting broad-band data such as that produced by multispectral scanners and thematic mappers aboard Landsat satellites.

For hyperspectral data, K is large and the energy for a given pixel is available as a finely quantized function of wavelength. Therefore the sample derivatives of energy with respect to wavelength can be estimated to provide additional statistics (Tsai & Philpot [73]). Efficient representations of hyperspectral data for specific types of analyses are also provided by various binary coding systems (Carlotto [10], Jia & Richards [42]).

Among statistical transformations, principal components analysis (PCA) is a standard tool for data compression and enhancement in many earth science fields. However, PCA may fail to order the component images according to decreasing signal-to-noise ratio because the signal has spatial structure or the noise has spectral structure. Modifications involve transforming the K-dimensional observations $Z_i=S_i+N_i$, where S_i is the signal of interest in the i^{th} pixel and N_i is noise, before applying principal components analysis. Given estimates of the covariance matrices of the measurements, Σ, and the noise, Σ_N, PCA can be applied to the noise-adjusted covariance matrix $F^T\Sigma F$, where $F^T\Sigma_N F = I$ (Green et al. [34], Lee et al. [50].) Orthogonal subspace projection (OSP) methods (Harsanyi & Chang [37]) require either knowledge or estimates of the spectral structure of the noise, so that PCA or noise-adjusted PCA can be carried out in the subspace orthogonal to the subspace defined by this interfering signal.

Statistical transformations can also be tailored using auxiliary information in the form of "ground truth" for some of the pixels in the image or spectral information about target elements. Given a training set, Tu et al. [74] use canonical correlation analysis for band selection. Jimenez & Landgrebe [43] optimize a transformation by projection pursuit, using a projection index that is a measure of separability of the target classes in the training set.

Clustering is another approach to data reduction and feature extraction. In the spectral domain, clustering generates a set of spectral classes, while in the spatial domain the result is a segmented image. Statistical methods for the spectral domain are generally flexible split-and-merge algorithms; see Simpson et al. [66], for example. Self-organizing feature maps are often used together with neural net classifiers; see for example Blonda et al. [7]. Ryan and Arnold [62] use vector quantization methods with optimal source coding, that is, optimization of the codebook vectors based on a training set with an appropriate metric. Image segmentation has been performed using wavelet-based multiresolution analysis (Csillag & Kabos [19]), region-growing methods (Lemoigne & Tilton [52]), neural networks (Chen et al. [13]), fuzzy sets (Cannon et al. [9]), Bayesian morphology (Forbes and Raftery [26]), and hierarchical random field models (Kelly et al. [45]).

Texture features provide a great deal of information to supplement the spectral characteristics of remote sensing data. Spatial fields of such features are used with or instead of spectral features in many applications. Gabor filters are used as bases for wavelet decomposition of imagery to extract texture information by many authors, e.g., Raghu & Yegnanarayana [58]. Texture has been characterized statistically using autocorrelation functions (Atkinson & Lewis [3]), fractal dimension (Chaudhuri & Sarkar [12]), and Markov random fields (Winkler [82]). Orientation of small linear features is summarized by rose diagrams, which in turn have characteristics such as elongation that can be mapped as a digital field (Zlatopolsky [84].) Tupin et al. [75] use a series of operators to extract spatial features from radar imagery.

THEMATIC MAPPING

The first task for most applications of remote sensing is classification of pixels or regions in the scene into information classes that are meaningful for the task. at hand. Unlike the spectral classes obtained by cluster analysis, useful information classes can generally be determined only with the use of a training set, so supervised classification methods are used.

Statistical algorithms include methods based on maximum likelihood or nearest-neighbor decision rules and classification trees. Maximum likelihood methods may require the estimation of separate covariance matrices for each class or may use a pooled covariance matrix. A particularly simple version that assumes the covariance matrix is the identity is called the "minimum distance classifier" in the remote sensing literature. Penalized discriminant analysis takes the high level of correlation among the variables

into account (Yu et al. [83]). A Bayesian interpretation of maximum likelihood allows Gorte & Stein [33] to update prior class probabilities and obtain unbiased estimation of class coverages. Friedl and Brodly [27] evaluate classification tree algorithms for remote sensing applications.

Feedforward networks (multilayer perceptron networks) used for classification have an input node for each discriminating variable and an output node for each class. Internal network structure (number and size of hidden layers) and parameters for the learning algorithm must be selected by the user. The training set is used to adjust the internal weights of the network by means of a learning algorithm such as backpropagation. While some of the literature suggests that neural nets may be able to learn on smaller data sets without dimension reduction, training sets must still be representative in order to obtain good results, and feature extraction may increase the interpretability of results and shorten the time required to train the network. In terms of accuracy, however, neural networks have been shown to perform favorably in comparison to most statistical methods in several studies such as Serpico et al. [64].

At the spatial scale of most remote sensing systems a pixel contains a mixture of materials or land cover types. Statistical and neural net classifiers typically produce hard classification results, that is, one pixel is assigned to one class. Both types of method could provide more information: posterior classification probabilities for each class are available from many statistical classifiers, and activation weights for each output node can be observed in a neural net. However, it is not always clear how to relate uncertainty in classification to the fraction of land cover present in a given pixel. Fuzzy classifiers which allocate every pixel to every class with varying grades of membership have also been proposed to address this problem more explicitly. Foody and Arora [25] point out that the mixed pixel problem needs to be accommodated not only in reporting classification results, but also in training and error estimation.

Supervised classification requires that a training set be available, consisting of pixels whose classification is known. As the number of dimensions in the data space (i.e., the number of spectral bands) increases, the number of training samples must also increase. Rules of thumb proposed by various authors indicate that the number of training samples per class should be 10 to 100 times the number of discriminating variables. Otherwise the overall performance of a classifier can actually degrade. (This is referred to as the "Hughes phenomenon", after Hughes [39].) Landgrebe and coworkers have experimented with several methods for alleviating this problem, including manual identification of training samples from spectral information alone (Hoffbeck and Landgrebe [38]) and the addition of unlabeled samples using an EM algorithm (Tadjudin and Landgrebe [70].) Other problems with training sets for remote sensing data include the difficulty of finding unmixed pixels and of ensuring that all of the classes of interest are represented. Mixed pixels can be removed from the training set (Arai [2]), but this exacerbates the problem of obtaining a sufficiently large training set. The presence of untrained classes may degrade the performance of a classifier (e.g., Foody [24].) On the other hand, Jeon and Landgrebe [41] were able to obtain satisfactory results for the case where training samples were available for only the class of interest.

The use of hybrid supervised/unsupervised classification methods effectively reduces dimension and thus both the training set requirements and computation times for the supervised portion of the algorithm. In these methods, unsupervised clustering is followed by labeling of the spectral classes (for example, by supervised majority voting.) Then the entire image is classified into the refined set of spectral classes by any of the standard supervised methods. Another type of hybrid algorithm classifies the regions of an over-segmented image instead of individual pixels.

Contextual classification methods make use of information from neighboring pixels as well as the spectral information associated with the pixel being classified. One large class of contextual methods performs post-classification revision of results from a first-pass classification based on examination of the classification of neighboring pixels (Mohn et al [55]). Revision methods range from simple voting algorithms within windows of fixed size to iterative spectral- and class-specific procedures. Probabilistic label relaxation methods start with a vector of probabilities for each pixel such as might be produced by maximum likelihood discriminant analysis and modify these iteratively based on the likelihood that pixels of two different classes will be found in the same neighborhood (Gong and Howarth [32]). Neighborhood

information is used directly in classification by the Iterated Conditional Modes algorithm (e.g., Cortijo & de la Blanca [17].) Solaiman et al. [67] develop a region-growing postprocessing algorithm.

Information that is useful for improving classification comes from other sources as well as the spatial context. Categorical information is available from existing thematic maps such as might be produced by conventional geologic field mapping. Much digital information is stored in geographic information systems (GIS). Human interpreters possess and use *a priori* knowledge about objects such as roads, rivers and building. These data, even if they are spatially referenced and digital, are frequently not on the same measurement scale as remote sensing data, or not stored using the same data base structures, or are not image data.

Two basic approaches to working with data from multiple sources can be distinguished. One is "data fusion" or "data integration", in which data from all sources are used simultaneously or sequentially to arrive at the ultimate classification. The other is "decision fusion", in which interpretations of data from the different sources are combined to make the final classification decision. Gong [31] compares evidential reasoning and neural networks for multisource data fusion. The data fusion method of Solberg et al. [68] is based on a Markov random field model. Le Hégarat-Mascle et al. [51] combine monosource classification results using evidential reasoning, deriving the required mass functions by an unsupervised method. Other common decision fusion method include weighted consensus methods, where the weights assigned to individual data sources reflect the reliability of those sources, and joint likelihood formalisms (Jeon and Landgrebe [40].) Benediktsson & Kanellopoulos [6] propose a two stage approach, in which the first stage requires either a majority or unanimity of the sources to agree on a classification, and the remaining samples are then classified in a second stage using a neural net.

Knowledge-based methods (expert systems and other rule-based systems such as semantic nets) have been applied to incorporate empirical knowledge into the classification process. Johnsson [44] used an expert system to improve the classification of built-up areas based on SPOT data, and Kruse et al. [48] included an expert system in a process to identify surface mineralogy from AVIRIS data. Tonjes et al. [72] created semantic nets to represent prior knowledge about landscape scenes as well as the imaging process to extract complex objects from multisensor imagery.

Given some "ground truth", the accuracy of classification is usually summarized in an error matrix (Congalton and Green [16]). This is a contingency table whose marginals correspond to the probability of misclassifying a pixel belonging to a given class (called the Producer's accuracy in remote sensing work), or of erroneously assigning a pixel to a given class (User's accuracy.) Among overall measures of error, the kappa coefficient of agreement, a measure of the deviation of the error matrix from the diagonal, is often reported. Foody [23] proposes the use of average distance measures that allow for fuzziness in both the training data and the classification results.

QUANTITATIVE ESTIMATION USING REMOTE SENSING DATA

For some applications, a thematic map may be less useful than estimates of the fraction of each cover type in each pixel. Linear mixture models are suitable for spectral unmixing of individuals pixels if the contributing components form a mosaic within the pixel but not if they are in such intimate association that electromagnetic radiation interacts with more than one end member as it is scattered from the surface. The linear mixture model takes the form $Z_i = M\pi_i + e_i$ where M is a $n \times c$ matrix whose columns are the (known) n-dimensional spectra of the c pure cover types or end members (Settle & Drake [65]). For a true mixture model the π_i are constrained to be positive and sum to one, but when the end member spectra are not well known it may be useful to relax these constraints.

The end member spectra may be derived from laboratory spectra (Drake et al. [21]) or ground-level field measurements. In practice it may be difficult to adjust these spectra to match the signal received at a remote sensor after passing through the intervening atmosphere, so other techniques have been devised to refine the end-members based on the data. Purely empirical methods such as convex hull analysis have been used (Craig [18]) but there is no guarantee that these will provide physically interpretable results. Two-step or iterative methods that solve for both M and the π_i, incorporating *a priori* knowledge about

both the spectra and cover type abundances in the starting model and in iteration constraints, are proposed by Tompkins et al. [71] and van der Meer [76]. Maselli [53] and Roberts et al. [61] customize the selection of end members from a large number of candidates on a pixel-by-pixel basis. Brown et al. [8] use support vector machines to select the relevant pure pixels.

Foody [23] and Bastin [4] evaluate fuzzy alternatives to the linear mixture model. Geostatistical methods are particularly useful when cover types grade into one another (Ahn et al. [1], van der Meer [77]). Roberts et al. [61] apply nonlinear mixture models. Image sharpening techniques combine spectral unmixing of multispectral data with the use of higher spatial resolution data to locate the end members more precisely (e.g., Gross & Schott [36]).

Hyperspectral instruments open up the possibility of identifying not only broad land cover types but also specific chemicals in a pixel or scene, using techniques that are based on the principles of reflectance spectroscopy (Goetz & Curtiss [29].) Typically, these methods require spectral libraries, which are available for minerals, soils and vegetation types. Most spectral matching algorithms begin by approximating the continuum of the spectrum, often by the convex hull of the measurements, and normalizing the measurements by the resulting function of wavelength (Green and Craig [35]). This isolates the absorption features from the overall reflectance properties of other components in the signal. Techniques for matching continuum-corrected spectra use binary coded data (Jia and Richards [42]), angular information (the Spectral Angle Mapper algorithm; see Kruse et al. [48]), or the complete spectrum via the cross-correlation algorithm of van der Meer and Bakker [78] or a least squares fitting procedures such as the Tricorder algorithm described by Clark and Swayze [14].

Many studies are designed to estimate changes in land cover proportions from remote sensing data. Swamy and Brivio [69] combine estimates of snow-covered areas with digital elevation models to obtain input for hydrological models of seasonal and real-time runoff in the Italian Alps. Piwowar and LeDrew [57] evaluate the potential of remote sensing data to address trends in sea ice extent. The use of remote sensing data for change detection in these and other applications requires accurate image registration (Dai & Khorram [20]). Radiometric matching methods have been developed to make a pair of images appear to have been collected under the same atmospheric and illumination conditions. Collins and Woodcock [15] suggest that simpler image-based normalization is adequate for commonly used linear change detection techniques.

Semi-empirical models form an integral component of recent methods for using remote sensing data in the estimation of geo- and biophysical parameters such as land and sea surface temperature, photosynthesis and evapotranspiration on regional and global scales. Olioso et al. [56] review a number of soil-vegetation-atmospheric transfer (SVAT) models and methods for driving them using remotely sensed data. Such models must be carefully designed to make accurate and optimal use of remote sensing information, as illustrated for example by Gastelli-Etchegorry and Trichon [28]. Goetz et al. [30] assess production efficiency models and show that surface variables recovered from satellite observations using such models are in good agreement with field measurements across a number of ecosystems.

FURTHER READING

NASA maintains an extensive remote sensing tutorial at http://rst.gsfc.nasa.gov/. This includes links to many other on-line educational resources as well as other types of sites related to remote sensing. Other useful sites relate to the Earth Observing System (http://terra.nasa.gov/ and http://earthobservatory.nasa.gov/) and include instructions for obtaining data. The USGS maintains a web site on remote sensing spectroscopy at http://speclab.cr.usgs.gov/. *Hyperspectrum* is a newsletter on imaging spectrometry at http://www.techexpo.com/WWW/optoknowledge/ .

Important reference works include the *Manual of Remote Sensing* (Ryerson [63]), now in its third edition, and the *Remote Sensing Data Book* (Rees [60]), organized as a dictionary with much good information and many basic formulas. Many textbooks have been written over the years; a short list is included on the overview page of the NASA tutorial. This article has concentrated on the analysis and use of remote sensing data, but the interested reader will easily find on-line and print resources dealing in

greater detail with the physical and engineering principles underlying the acquisition of these data (e.g., Kramer [47], Rees [59].)

Several major journals are devoted to remote sensing, including the *International Journal for Remote Sensing, Remote Sensing of Environment, Photogrammetric Engineering and Remote Sensing, Canadian Journal of Remote Sensing , ISPRS Journal of Photogrammetry and Remote Sensing,* and *IEEE Transactions on Geoscience and Remote Sensing*. The last of these has frequent special issues providing overviews of special topics such as data fusion (May 1999) and on the extraction of bio- and geophysical parameters from SAR data (March 2000.) Articles on remote sensing appear regularly in other journals such as *Progress in Physical Geography, Ecological Modelling, Computers and Geoscience* and *Journal of Geophysical Research*, and in the pattern recognition literature.

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